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ORIGINAL RESEARCH

Predicting mid-term survival of patients during emergency department triage for resuscitation decision

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Abstract

In patients with non-small cell lung cancer (NSCLC) visiting the emergency department (ED), clinical decisions must be made based on their disease prognosis. This study aims to predict the disease outcome of patients visiting the ED for the first time after NSCLC diagnosis. This study included patients who visited the ED in 2016–2020 after being diagnosed with NSCLC in study site or within 30 days before the first outpatient clinic visit after diagnosis. Primary outcome of prediction model was 3-month mortality from the initial ED visit. We analyzed the association between outcome and each variable as a risk factor and built a prediction model using these variables. Both oncologic factors and ED-associated factors were associated with the 3-month mortality of NSCLC from the first ED visit. We also visualized the treatment trace as a sequence and utilized it in prediction model building. The areas under the receiver operating curve (AUROCs) of the prediction model of 3-month mortality from the first ED visit ranged from 0.677 (95% Confidence Interval (CI), 0.640–0.708) to 0.729 (95% CI, 0.697–0.761). This study provides the prediction model about 3-month survival in first ED visit point and identified patient and disease-related factors to predict the prognosis of patients.

Keywords

Non-small cell lung cancer; Emergency department; Prognosis; Machine learning

1. Introduction

Among cancer, lung cancer, especially non-small cell lung cancer (NSCLC) is the most common and frequently leads to acute illness [1–3]. Emergency department (ED) visits by cancer patients are increasing, and lung cancer patients often visit the ED with critical status [4, 5]. More than 10% of lung cancer patients require care in the intensive care unit (ICU), a rate that is increasing annually [2, 6].

Due to its severity and prevalence, studies have analyzed and predicted the survival and prognosis of NSCLC and lung cancer [7, 8]. Some of these studies have focused on terminal-stage cancer [1, 5, 9]; others have focused on biomarkers or genetic characteristics associated with lung cancer prognosis [8, 10]. Finally, studies have also identified risk factors related to worse outcomes and applied deep learning techniques to predict patient survival and disease prognosis [11, 12].

Especially in the ED, clinical decision-making in patients with underlying diseases such as lung cancer must consider their disease prognosis to avoid unnecessary life-sustaining treatment, improve patient quality of life, and reallocate ED resources to patients requiring acute care [5]. Moreover, patients want to make decisions based on their prognosis and avoid useless or painful treatments, while ED clinicians face limited resources, with urgent patients presenting to the ED at every moment and a need to focus on patients who are most critical and expected to benefit most from treatment while also respecting patient wishes [13, 14]. Therefore, rapid decision-making regarding life-sustaining treatments or resuscitation plans in patients with underlying diseases such as lung cancer is based on patient disease status and prognosis when the patient visits the ED.

However, few studies provide the practical information needed in early decision-making, when lung cancer patients are acutely ill and visit the ED. Patients with cancer may experience symptoms caused by the disease or adverse treatment effects, for which they visit the ED [2, 5, 15]. In the ED, patients and clinicians must make prompt decisions about their emergency treatment, which is often painful and does not improve disease prognosis [5, 16]. Making these acute and critical decisions requires information on disease prognosis based on both the patient's medical history and the present status of the ED to establish a cancer patient treatment plan.

This study analyzed data from patients with lung cancer who visited the ED for the first time after diagnosis to predict disease outcomes and support treatment planning in the ED.

2. Methods

This study was designed and explained followed by transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) statement and other previous study [17, 18].

2.1 Study Setting and Population

This retrospective study was conducted in the ED of a tertiary hospital located in a metropolitan city. The hospital has approximately 1960 inpatient beds. Approximately 80,000 patients visit the ED annually. This study included patients who visited the ED from 1 January 2016 to 31 December 2020.

The study included patients who visited the ED after a diagnosis of NSCLC in a hospital or who were diagnosed within 30 days before the first outpatient clinic visit after diagnosis. We searched for patients diagnosed using the International Classification of Disease version-10 (ICD-10) code. We excluded patients with small cell lung cancer and those who visited another center 30 days after the diagnosis of lung cancer.

2.2 Selection of Predictors

Patient demographic information, including age and sex, is used to construct prediction models. Systolic blood pressure, diastolic blood pressure, pulse rate, respiratory rate, body temperature at arrival, and oxygen saturation were all recorded during the ED visit. Additionally, the Korean Triage and Acuity Scale (KTAS) was included as an input variable. The KTAS is a five-level triage scale based on the patient's principal complaint and symptom severity. The AVPU (Alert, response to Verbal stimuli, response to Pain stimuli, Unresponsiveness) scale, which measures mental state in reaction to stimuli, was used as an input variable. The AVPU is a four-level scale system that is divided into four categories: alertness, responsiveness to verbal stimuli, responsiveness to pain stimuli, and unresponsiveness. Finally, the mode of arrival was included in the input variable, which was separated into two categories: patients who arrived via ambulance and those who did not.

Additionally, patient oncologic data were collected on the disease state of NSCLC and the therapy process. This data included the date of NSCLC diagnosis; the stage of NSCLC at diagnosis; the kind and date of operation; the number, date, and location of radiotherapy (RT) treatments received; and the number and dates of chemotherapy regimens administered.

2.3 Data Extraction and Preparation

Patient clinical, ED visit, and oncologic information were extracted from the Clinical Data Warehouse (CDW) DARWIN-C (Data Analytics and Research Window for Integrated Knowledge C) of study site. CDW encrypts and stores electronic medical records, medical test results, and medication information recorded as logs of Data Analytics and Research Window for Integrated Knowledge C of the study site. These records can be extracted through the use of encrypted patient identification.

For the sake of readability and nonlinearity, several continuous variables were turned into categorical variables. The ages of participants were classified as 18–40 years, 40–60 years, 60–80 years, and others. The form of transport used to arrive was classified as public ambulance, private ambulance, or other. The route of entry was established by direct admission, transfer, and other means.

Vital sign information was categorized as normal and abnormal. A systolic blood pressure of 100–150 mmHg, diastolic blood pressure of 60–90 mmHg, pulse rate of 50–100 bpm, respiratory rate of 12–20/min, body temperature of 36–37.5 °C, and O_2 saturation of 95–100% were categorized as normal; values outside the normal ranges or not available (NA), were categorized as abnormal [19, 20]. Missing values for vital signs and stage were assigned a value of "NA" (not available), which indicated missingness for some reason such as severe patient condition. Therefore, we categorized NA vital signs as abnormal. As outcome information, we collected discharge information, including discharge to home, ED death, transfer, and admission. We also recorded the place where admission information was collected, including the ICU and general ward (GW).

Preprocessing of NSCLC-related data was performed using their timestamp data. NSCLC diagnosis; NSCLC stage at diagnosis was determined based on their earliest report in the studied site. The type and date of operation, the number, date, and location of radiotherapy (RT) treatments received and the number and dates of chemotherapy regimens delivered were gathered separately each time they were administered.

2.4 Sequences of Oncologic Treatments

We described the sequence of treatment and patterns from the first diagnosis, operation, chemotherapy, radiotherapy, and ED visit or death. The different activity sequences were visualized using the bupaR package in R to explore the most frequent patterns of ED visits among patients with NSCLC. We built a trace of each patients with this sequence. Also, we divided traces into 4 groups refer to hazard ratio.

2.5 Prediction Model

We built the prediction model from a total of 3478 NSCLC patients visiting the ED between 1 January 2016, and 31 December 2020. Electrical medical record data elements, including the outpatient visit history, patient demographic information, ED visit information, and oncological information described above, were used for model development.

We randomly selected 70% of the patients for model development and reserved 30% for model validation. To obtain the best hyperparameters, a random search was performed on 10-fold cross validation. We considered maximum tree depth, minimum numbers of data in a node, number of predictor and learning rate for extreme gradient boost (XGB) and Random Forest (RF), penalty weight for logistic regression (LR) and number of hidden unit and layers for Artificial Neural Network (ANN) to optimize the performance.

We implemented four machine learning (ML) methods for predicting 3-month mortality from ED visit outcomes in the training dataset: LR with L2 penalization, RF, XGB, and deep learning. To obtain the best hyperparameters, a grid

search was performed for each classifier. We calculated areas under the receiver operating curve (AUROCs) and areas under the precision-recall curve (AUPRCs) for each model on the validation datasets. To obtain the 95% confidence intervals (CI), we implemented 1000 bootstraps for each metric.

The software implemented for model development and validation were R (version 4.1.0), Python (version 3.8.5, R foundation) and Tensorflow framework (version 2.3.1, Python software foundation)). The following packages were used: xgboost (version 1.4.1.1), randomForest (version 4.6-14), tidymodels (version 0.1.4) in R and scikit-learn (version 0.23.2) in Python.

2.6 Outcomes

Our primary outcome was mortality within 3-months of the initial ED visit, which was the target feature for analysis to build the model. We also evaluated the 1-year, 1-month, and 1-week mortality rates from the initial ED visit as a secondary outcome.

2.7 Local Interpretation of Result

We also tried to introduce the Shapely additive explanation (SHAP) method which is an extension of local interpretable model-agnostic explanations to express reason of prediction result locally, with package "shap". This package helps to illustrate risk factors which contributes to outcome [21].

2.8 Statistical Analysis

The data are presented as means ± standard deviation (SD) for continuous variables and as frequencies (%) for categorical variables. Comparisons were performed using t-test and chi-square tests at a 5% significance level. The statistical analysis for the hazard ratio of variable to 3-month mortality was performed using multiple-survival cox regression. We selected variables that showed significance in univariate cox regression analysis at a 5% level of significance. The software implemented for model development and validation were R (version 4.1.0), python programming language (version 3.8.5), tensorflow framework (version 2.3.1), and scikit-learn (version 0.23.2).

3. Results

During the 4-year study period from 2016, 15,680 patients were added to the lung cancer registry. Among them, 12,068 patients were diagnosed with NSCLC and 10,709 were first diagnosed at the study center. From this population, 3478 patients visited the ED after the diagnosis and were included in the final analysis (Fig. 1). Among these patients, the 3-month mortality rate was 17.9% (624 patients). Most of patient included in study was over 60 years (62.2% and 66.5%, respectively). The ratios of male patients and abnormal vital signs were higher in the outcome (3-month mortality) group. The KTAS and mental status at the first ED visit also differed between groups. Regarding oncological information, the ratio of patients with stage 4 cancer was higher in the outcome (mortality at 3 months) group. The patient demographic characteristics are summarized in Table 1. The top 16 treatment traces, which comprise 50% of all traces, are shown in Fig. 2.

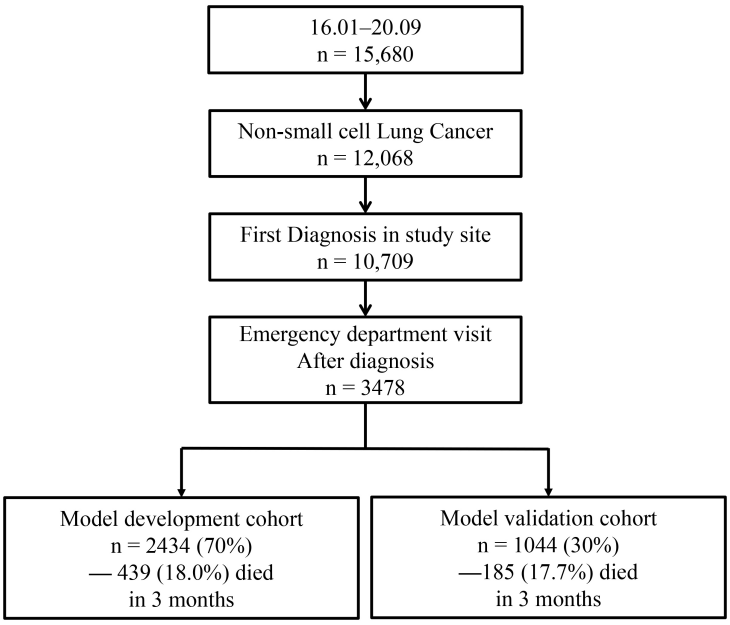

FIGURE 1. Flow chart of the population of patients visiting the emergency department in 20162020 after a diagnosis of non-small cell lung cancer at study site.

Table 2 shows the results of the analysis of risk factor associated with 3-month mortality inferred from cox hazard regression with adjusted univariate and multivariate analyses. Not only oncologic information such as stage and presence of operation, RT, and chemotherapy but also patient demographic information and ED visit-related information, such as vital sign, visit method, mental status, were associated with 3-month mortality ($p < 0.001$). Stage, especially 4 or unknown was associated with 3-month mortality (hazard ratios (HR): 2.03 and 2.50; 95% CI: 1.38–2.96 and 1.69–3.70). Fig. 3 summarizes the AUROCs according to the prediction method for each outcome with 95% CI. The AUROCs ranged from 0.677 (95% CI, 0.640–0.708) to 0.729 (95% CI, 0.697–0.761) and the AUPRC ranged from 0.339 (95% CI, 0.289–0.392) to 0.401 (95% CI, 0.343–0.462).

Table 3 shows the distribution of triage results for the KTAS and the occurrence probability of ML-based 3-month mortality. The cutoff value for the ML probability was determined according to the quintile of the outcome probability. The results show the relationship between the KTAS and 3-month mortality. The ratio of a high probability of death was the highest (71.43%) in patients with KTAS 1. As the KTAS increased, the ratio of the population with a higher probability of death increased.

Table 4 shows detail patients who were given a Do Not Resuscitate (DNR) order and the outcome of a three-month survival prediction. In addition to the patients who died within three months, 154 patients were projected to die in our model but did not have a DNR order.

TABLE 1. Characteristics of the groups of patients who survived and died within 3 months from the first ED visit after a new diagnosis of non-small cell lung cancer.

	Patients who survived (n = 2854)	Patients who died within 3 months (n = 624)	[a]*p*-value
Age group (years), n (%)			<0.001
18–40	60 (2.1%)	7 (1.1%)	
40–60	841 (29.5%)	131 (21.0%)	
60–80	177 (62.2%)	415 (66.5%)	
80 and over	176 (6.2%)	71 (11.3%)	
Sex, n (%)			<0.001
Male	1866 (65.4%)	477 (76.4%)	
Female	988 (34.6%)	147 (23.6%)	
SBP (mmHg)			0.009
100–150	2115 (74.1%)	430 (68.9%)	
[b]out of ref	739 (25.9%)	194 (31.1%)	
DBP (mmHg)			0.006
60–90	2079 (72.8%)	420 (67.3%)	
[b]out of ref	775 (27.2%)	204 (32.7%)	
PR (beats/min)			<0.001
50–120	2196 (76.9%)	403 (64.6%)	
[b]out of ref	658 (23.1%)	221 (35.4%)	
RR (breaths/min)			<0.001
12–20	2456 (86.1%)	445 (71.3%)	
[b]out of ref	398 (13.9%)	179 (28.7%)	
Temperature (°C)			0.086
36–37.5°C	2146 (75.2%)	448 (71.8%)	
[b]out of ref	708 (24.8%)	176 (28.2%)	
SpO_2(%)			<0.001
95–100	2459 (86.2%)	410 (65.7%)	
[b]out of ref	395 (13.8%)	214 (34.3%)	
KTAS, n (%)			<0.001
1	13 (0.5%)	20 (3.2%)	
2	141 (4.9%)	77 (12.3%)	
3	1529 (53.6%)	368 (59.0%)	
4	1048 (36.7%)	149 (23.9%)	
5	123 (4.3%)	10 (1.6%)	
Mental status, n (%)			<0.001
Alert	2824 (98.9%)	596 (95.5%)	
Response to verbal output	14 (0.5%)	10 (1.6%)	
Response to pain	11 (0.4%)	9 (1.4%)	
Unresponsive	5 (0.2%)	9 (1.4%)	
Mode of arrival, n (%)			<0.001
Ambulance	203 (7.1%)	72 (11.5%)	
Other	2651 (92.9%)	552 (88.5%)	

TABLE 1. Continued.

	Patients who survived (n = 2854)	Patients who died within 3 months (n = 624)	[a]*p*-value
stage, n (%)			<0.001
1	556 (19.5%)	43 (6.9%)	
2	216 (7.6%)	27 (4.3%)	
3	723 (25.3%)	115 (18.4%)	
4	891 (31.2%)	258 (41.3%)	
NA	468 (16.4%)	181 (29.0%)	
LOS (days), mean ± SD	11.9 ± 13.5	18.0 ± 18.0	<0.001
Discharge, n (%)			<0.001
Home	1766 (61.9%)	217 (34.8%)	
ED death	0 (0.0%)	19 (3.0%)	
Transfer	70 (2.5%)	31 (5.0%)	
Admission	1018 (35.7%)	357 (7.2%)	

[a]p-values are calculated by independent t-tests for continuous variables and chi-square test for categorical variables; [b]out of ref: outside of the reference range, not available, or not-recorded. Abbreviations: SD—standard deviation; SBP—systolic blood pressure; DBP—diastolic blood pressure; PR—pulse rate; RR—respiratory rate; SpO_2—peripheral capillary oxygen saturation; KTAS—Korean Triage Acute Scale; LOS—length of stay; ED—emergency department.

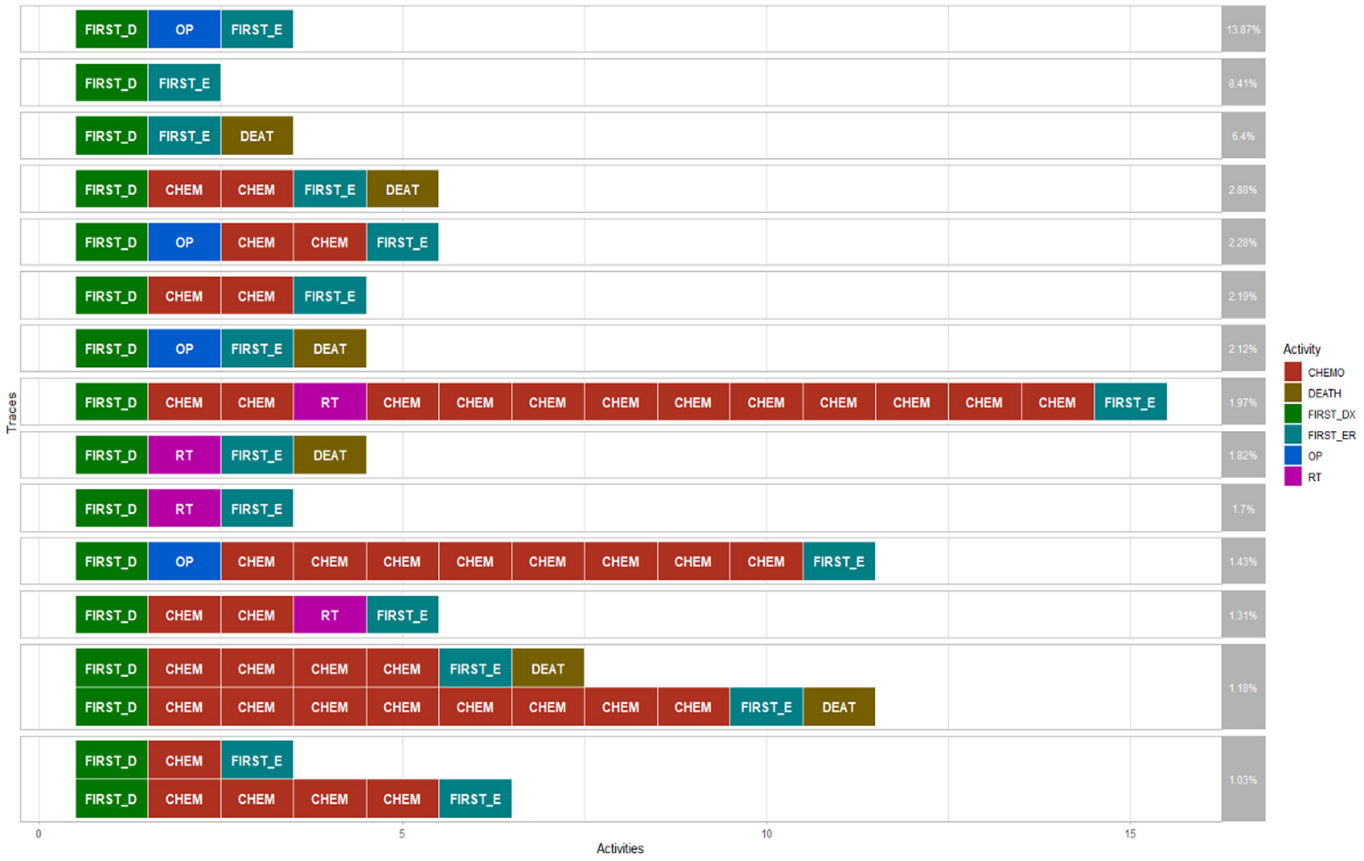

FIGURE 2. Top 16 treatments administered between first diagnosis and the first ER visit, as identified through process mining. FIRST_D—First diagnosis; CHEM—Chemotheraphy; FIRST_E—First ER visit; RT—Radiotheraphy; OP—operation; DEATH—Death.

TABLE 2. Factors associated with 3-month mortality outcome inferred from cox hazard regression with adjusted univariate and multivariate analyses.

Variables	n	Univariate Analysis			Multivariate Analysis		
		HR	95% CI	*p*-value	HR	95% CI	*p*-value
Age	3478			<0.001			
18–40	67	1([a]ref)			1([a]ref)		
40–60	972	1.34	0.63–2.86		1.56	0.73–3.36	0.252
60–80	2192	1.95	0.92–4.12		2.31	1.09–4.92	0.029
80 and over	247	3.19	1.47–6.93		3.36	1.53–7.4	0.003
Sex							<0.001
Female	1135	1([a]ref)			1([a]ref)		
Male	2343	1.65	1.37–1.99	<0.001	1.53	1.26–1.85	
KTAS				<0.001			
3	1897	1([a]ref)			1([a]ref)		
1	33	5.65	3.60–8.86		2.7	1.51–4.83	0.001
2	218	2.18	1.71–2.79		1.46	1.11–1.91	0.007
4	1197	0.61	0.50–0.73		0.92	0.75–1.12	0.395
5	133	0.35	0.19–0.67		0.58	0.31–1.09	0.09
Mental status				<0.001			
Alert	3420	1([a]ref)			1([a]ref)		
Response to verbal output	24	3.06	1.64–5.72		1.75	0.9–3.41	0.1
Response to pain	20	3.5	1.81–6.76		1.52	0.75–3.05	0.242
Unresponsive	14	8.87	4.59–17.14		1.93	0.84–4.43	0.122
Visit by ambulance	275	1.63	1.28–2.09	<0.001	1.66	1.26–2.17	<0.001
Direct visit	2304	0.66	0.56–0.77	<0.001	0.72	0.61–0.86	<0.001
SBP (mmHg)				0.005			0.789
100–150	2545	1([a]ref)			1([a]ref)		
[b]out of ref	933	1.27	1.07–1.50		1.03	0.85–1.24	0.789
DBP (mmHg)				0.003			
60–90	2499	1([a]ref)			1([a]ref)		0.079
[b]out of ref	979	1.28	1.08–1.51		1.18	0.98–1.43	
PR (beats/min)				<0.001			0.005
50–120	2599	1([a]ref)			1([a]ref)		
[b]out of ref	879	1.77	1.50–2.08		1.3	1.08–1.56	

TABLE 2. Continued.

Variables	n	Univariate Analysis			Multivariate Analysis		
		HR	95% CI	*p*-value	HR	95% CI	*p*-value
RR (breaths/min)				<0.001			0.003
12–20	2901	1([a]ref)			1([a]ref)		
[b]out of ref	577	2.33	1.96–2.77		1.36	1.11–1.67	
Temperature °C				0.049			0.166
36–37.5	2594	1([a]ref)			1([a]ref)		
[b]out of ref	884	1.19	1.00–1.41		0.88	0.73–1.06	
SpO_2 (%)				<0.001			<0.001
95–100	2869	1([a]ref)			1([a]ref)		
[b]out of ref	609	2.9	2.45–3.42		1.87	1.54–2.26	
Stage				<0.001			
1	599	1 (ref)			1 (ref)		
2	243	1.58	0.97–2.56		1.03	0.63–1.69	0.911
3	838	1.99	1.40–2.83		1.03	0.68–1.54	0.896
4	1149	3.38	2.44–4.67		2.03	1.38–2.96	<0.001
unknown	649	4.43	3.18–6.18		2.5	1.69–3.7	<0.001
OP	3478	0.46	0.37–0.56	<0.001	1.55	1.19–2.04	0.001
RT	3478	1.24	1.05–1.46	<0.001	1.35	1.10–1.65	0.005
Chemotherapeutic agent							
Carboplatin	462	1.09	1.04–1.13	0.002	1.04	0.98–1.12	0.209
Cisplatin	1359	1.05	1.02–1.09	0.002	1.04	0.99–1.09	0.162
Docetaxel	124	1.14	1.06–1.21	<0.001	1.04	0.96–1.14	0.32
Etoposide	43	1.02	0.80–1.30	0.859			
Gemcitabine	350	1.14	1.08–1.19	<0.001	0.98	0.92–1.06	0.655
Other	951	1.01	0.99–1.02	0.341			
Paclitaxel	680	0.98	0.94–1.03	0.526			
Pemetrexed	640	1.03	1.02–1.05	<0.001	0.97	0.90–1.04	0.319
Vinorelbine	213	0.93	0.82–1.06	0.278			

[a]ref—reference; [b]out of ref—outside of the reference range, not available, or not-recorded;
One patient can use more than one chemo agents.
Abbreviations: HR—hazard ratio; CI—confidence interval; KTAS—Korean Triage and Acuity Scale; AVPU—alert, verbal, pain, unresponsive; SBP—systolic blood pressure; DBP—diastolic blood pressure; PR—pulse rate; RR—respiratory rate; SpO_2— peripheral capillary oxygen saturation; OP—Surgical operation; RT—radiotherapy.

TABLE 3. Three-month mortality probability grades according to KTAS.

KTAS	Probability grade					Total
	1	2	3	4	5	
1	1 (14.29)	0 (0.00)	0 (0.00)	1 (14.29)	5 (71.43)	7 (100.00)
2	5 (7.94)	9 (14.29)	0 (0.00)	14 (22.22)	35 (55.56)	63 (100.00)
3	52 (9.54)	109 (20.00)	119 (21.83)	131 (24.04)	134 (24.59)	545 (100.00)
4	112 (28.35)	103 (26.08)	78 (19.75)	71 (17.97)	31 (7.85)	395 (100.00)
5	13 (38.24)	10 (29.41)	8 (23.53)	2 (5.88)	1 (2.94)	34 (100.00)
Total	183 (17.52)	231 (22.12)	205 (19.63)	219 (20.97)	206 (19.73)	1044 (100.00)

Abbreviation: KATS—Korean Triage and Acuity Scale.
Values are presented as number (%).

Fig. 4 illustrates the output of a personalized dashboard. Patients A and B are expected to die within three months by this model, however patients C and D are not. For instance, patient A has a high chance due to his or her length of stay (LOS), abnormal pulse rate (PR CAT Abnormal), stage 4, and final KTAS value of greater than 4. Patient C is at low risk due to the year of surgery, normal saturation and pulse rate, and the fact that the final KTAS was less than 4.

4. Discussion

The results of this study demonstrated the prediction of patient outcome at the patient's first visit to the ED after diagnosis. This visit is generally the first time a patient has symptoms and requires immediate clinical decision-making, and supports a treatment plan based on disease prognosis. This model uses patient information that can be obtained in the first visit to the ED and decision-making in the early stage of the visit and, therefore, early decision-making. Thus, the findings of, this study helps ED clinicians to make treatment plans based on not only anticipated ED outcomes but also the prognosis of patients beyond the ED stage and further support the treatment selection and prioritization among patients in the ED.

In addition, as this study focused on patient prognosis, the results help patients end-of-life planning. This study predicted the outcome of a patient at their first visit to the ED, which is generally the first time a patient experiences subjective symptom, at a relatively early time-line of patient diseases. Early discussions and decisions about patients' treatment and end-of-life plans are associated with better quality of life and satisfaction [22, 23]. This study can support early decision-making for patients and clinicians and can reduce unnecessary treatment in the ED as well as the preparation of end-of-life care.

In addition to known oncologic-related factors, the results of this study showed that the patient initial ED status, which was not directly related to patient lung cancer status, was closely related to patient prognosis. ED visits might be related to symptom onset or aggravation. Therefore, the point at which patients visit the ED visit is another factor of follow-up in the disease process. In addition, both patient status at the ED visit and the number of visits were related to patient prognosis, indicating that the quantity and quality of acute aggravation of patient status are related to patient prognosis.

The length and timepoints for survival prediction also need to be modified according to patient status and prognosis. Therefore, our study provided several survival durations because each patient has different survival and prediction power varies by prediction point. Conversely, many time points of prediction are needed, with re-evaluation and re-prediction based on patient status. Not only the first visit but also subsequent ED visits can be checkpoints for the evaluation and prediction of patient prognosis. Additional possible factors for the evaluation and prediction of disease prognosis include admission, operation, or other events.

The information obtained in this study is helpful for patient-clinician discussions regarding life-sustaining treatment decisions. Most patients want to play a role in setting their treatment plans [24]. However, patients and their families often feel that they do not receive enough information or informed consent regarding their treatment [25]. This situation may be worse in the ED as clinicians may have limited information on the patient because most clinicians seeing patients in the ED are not the patient's main doctor, and a rapport between the patient and clinician has not yet been established. Despite these circumstances, lung cancer patients generally first visit the ED, due to their symptoms or illness. Therefore, the findings of this study might provide information about disease state and prognosis in the ED to assist in shared decision-making between clinicians and patients. Additionally, our study's results can be shown individually, which assists both the patient and physician in comprehending the prediction's outcome and may aid in communication.

According to our investigation, only half of the patients who died in 3 months after the ED visit received a DNR order. Quality of life and end-of-life decision making is an essential issue in cancer patients, and ED presentation is one of the time points of their decision making [5, 26, 27]. Survival prediction in ED first visit might be helpful for the early idea about the end-of-life planning and support discussion between patient, families, and physician.

This single-center, retrospective study might have had selection bias. To minimize bias, we included patients who had only received their first diagnosis at the study center. Second, we did not include cancer-related factors such as genetic mutations or treatment response. Instead, we considered information on chemotherapeutic agent use and treatments by sequence building. Finally, we did not include laboratory results, which can

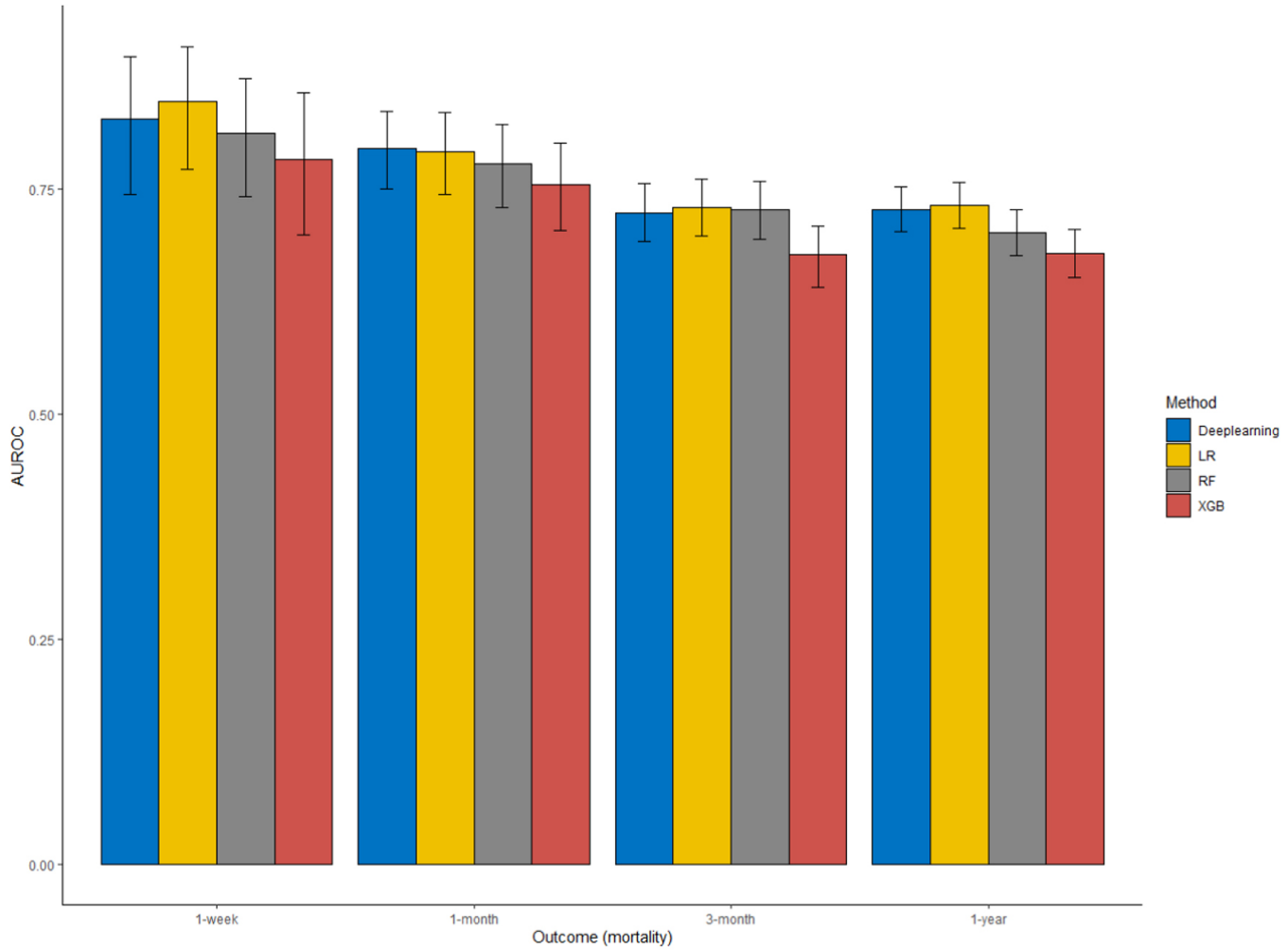

FIGURE 3. Areas under the receiver operating characteristic curves (AUROCs) with confidence intervals for each outcome and prediction method. LR—logistic regression with L2 penalization; RF—random forest; XGB—extreme gradient boost.

TABLE 4. Patent with DNR order and prediction result.

	Patient who did not received DNR order[a]	Patient who received DNR order
Number of patients predicted to be survived after 3 months	1315	144
Number of patients predicted to be death after 3 months	489	371
In patients who died in 3 months. (n = 515)		
Number of patients predicted to be survived after 3 months	86	64
Number of patients predicted to be death after 3 months	154	211

[a] *at 3-month period. Cut-off value used in prediction was calculated by Youden index.*
Abbreviation: DNR—Do Not Resucitate.

provide additional information about ED status. We excluded this information for future practical use of this model to predict patient prognosis in the early stage of ED visits and allow early decision-making.

Further study is needed on prognosis visualization to allow effective and practical information sharing, especially with patients. In addition, the prediction of each treatment option requires further study to provide specific and focused treatment suggestions.

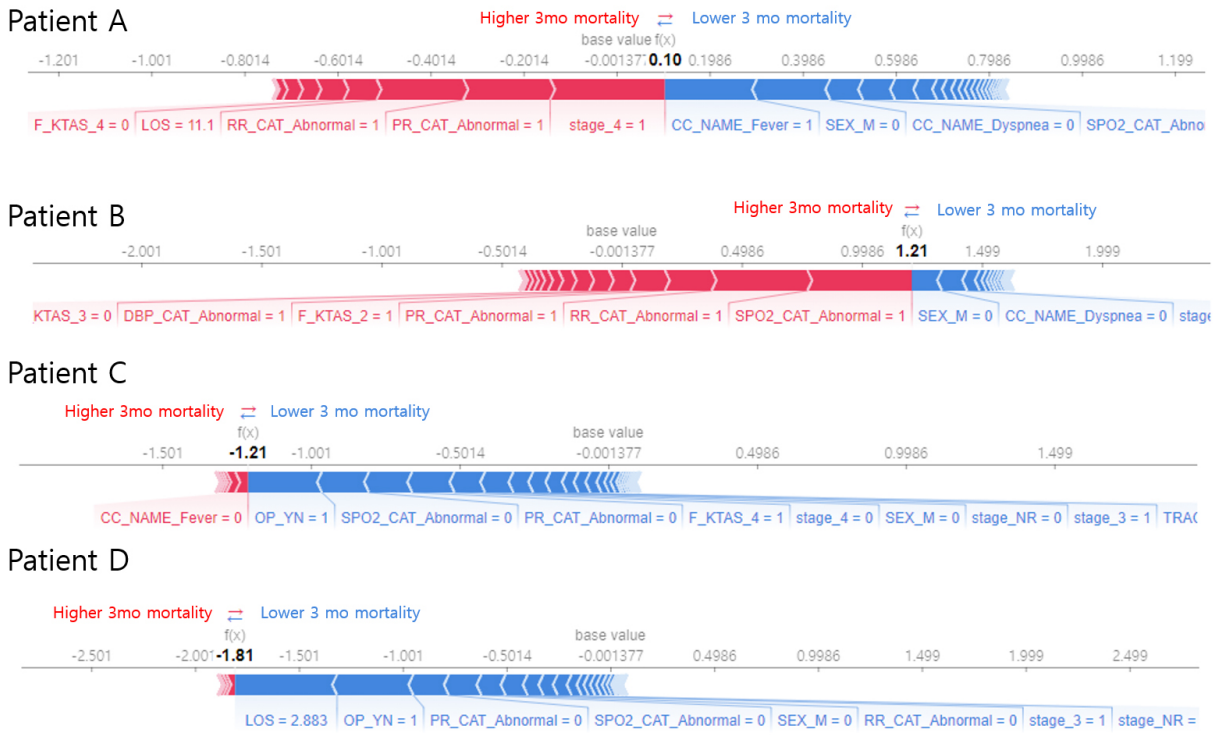

FIGURE 4. Illustration of individualized prediction result by risk factor. This illustration explains reason of risk of outcome occur (three-month death) individually by features.

5. Conclusion

This study provides the prediction model about 3-month survival in first ED visit point based on each patient factor related to disease status as well as factors related to patient status during ED visit. The results of this study provide information about the risk factors associated with the prognosis of patients with NSCLC at their first ED visit and established a prediction models. Not only the disease but also the patient status at the ED visit were related to the disease outcome. Several checkpoints are needed for a more accurate prognosis, of which the first ED visit might be one.

ABBREVIATIONS

NSCLC, non-small cell lung cancer; ED, Emergency Department; ICU, Intensive Care Unit; IRB, Institutional Review Board; KTAS, Korean Triage and Acuity Scale; RR, Respiratory Rate; NA, Not Available; GW, General Ward; RT, radiotherapy; ML, machine learning; LR, logistic regression; RF, random forest; XGB, extreme gradient boost; AUROC, areas under the receiver operating curve; AUPRC, areas under the precision-recall curve; CI, 95% confidence intervals; SD, Standard Deviation; SHAP, Shapely additive explanation; HR, Hazard Ratios; CDW, Clinical Data Warehouse

AUTHOR CONTRIBUTIONS

JYY and HC contributed equally to this work. Conceptualization, HC, JYY and WCC; Methodology, HC, JYY, and WCC; Validation, HC, SH, GTL, JEP, SUL, TK, SYH, HY and WCC; Formal Analysis, JYY and WJ. Data Curation, HC, WJ and JYY; Writing–Original Draft Preparation, HC and JYY; Writing–Review and Editing, TK, SYH, HY, and WCC; Visualization, HC and JYY; Supervision, TGS, MSS, IJJ, and WCC. All authors have read and given the final approval of the version of the manuscript to be published. All authors made a substantial contribution to the concept and design of the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Institutional Review Board (IRB) of Samsung Medical Center (IRB No. 2021-03-092), which waived the requirement for informed consent because of the retrospective, observational, and anonymous nature of the study.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. Won Chul Cha is serving as one of the Editorial Board members of this journal. We declare that Won Chul Cha had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to SF.

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